Optimization of Warpage Defects of Base Pencil Box by Using Backpropagation Neural Network and Genetic Algorithm

[1,2] Eko Ari Wibowo
[1] Department of Mechanical Engineering
Astra Manufacturing Polytechnic
[2] Master of Mechanical Engineering
Swiss German University
Tangerang City, Indonesia
arie.wibo07@gmail.com

Edi Sofyan
Master of Mechanical Engineering
Swiss German University
Tangerang City, Indonesia
edi.sofyan@lecturer.sgu.ac.id

Ary Syahriar
Department of Electrical Engineering
Al Azhar Indonesia University
Tangerang City, Indonesia
ary.syahriar@lecturer.sgu.ac.id

[1,2] Albertus Aan Dian Nugroho
[1] Department of Mechanical Engineering
Astra Manufacturing Polytechnic
[2] Master of Mechanical Engineering
Swiss German University
Tangerang City, Indonesia
albertus.aan@gmail.com

[1,2] Fuad Widiatmoko
[1] Department of Engineering
Infinitigroup
[2] Master of Mechanical Engineering
Swiss German University
Tangerang City, Indonesia
fuadwi@hotmail.com

[1,2] Paulus Gagat Charisma Arwidhiatma
[1] Department of Technical Support
PT. Trias Indra Saputra
[2] Master of Mechanical Engineering
Swiss German University
Tangerang City, Indonesia
paulusgagat@gmail.com

Abstract*—The use of plastic products is increasing rapidly nowadays, starting from automotive components, electronics, to office equipment. Injection molding process is a method of making plastic products by injecting the material into the mold. One of the products is a pencil box, but this product has a warpage defect. Defect is indicated by a deflection in the wall, causing misassembles. This study aims to eliminate these defects with parameter optimization. The L_{27} (3^4) orthogonal array was used to make the data input design. Data that has been designed is simulated by using MoldFlow to get the value of deflection. Results of the experiment were analyzed by using Backpropagation Neural Network to determine the pattern of relationship between process parameters and response, while Genetic Algorithm method was used for parameter optimization. The composition of the recommended parameters were mold temperature of 15°C, melt temperature of 200°C, packing pressure of 120% and injection time of 6 seconds. As a result, the optimization of deflection reached 44%. The previous maximum deflection of 2.779 mm has decreased to 1.554 mm.

***Keywords*—Plastic injection molding, Warpage defect, Backpropagation Neural Network, Genetic Algorithm**

I. Introduction

The use of plastic is now increasingly massive, marked by the amount of plastic production currently reaching more than 230 million tons/year and it continues to increase this year to 400 million tons with a growth rate of around 5% per year [1, 2]. There is a study that states the consumption of raw material is based on weight, which is plastic when compared with other materials such as aluminum, steel, rubber, copper, and zinc. This is reasonable because plastic is easy to form and low in processing costs [3]. Plastic products are also increasingly varied, because of their easily constrained nature, cheap production processes, and increasing physical properties.

Pencil box is one of the types of equipment used as a place to store stationery. The pencil case consists of two components namely: a cover and a base. One indicator of the quality of a pencil box is that the quality of the assembly between the components must be tight when closed. However, in reality the product cannot be assembled properly. So, it does not pass the quality test and cannot be sold. This is caused by warpage defects in each component. Warpage defect is another form of distortion, it is caused by a different shrinkage in the product surface. Where if one area or direction of filling experiences a different level of shrinkage from the area or other filling direction, the part will be curved [4]. One of the main factors causing warpage is non-uniform shrinkage. The cause of the non-uniformity of shrinkage is due to the following conditions: material characteristics, differential orientation, differential cooling, differential crystallinity, differential thermal strain, mold condition [5]. Fig. 1 shows that the defect condition of the product is misassembled when it is closed.

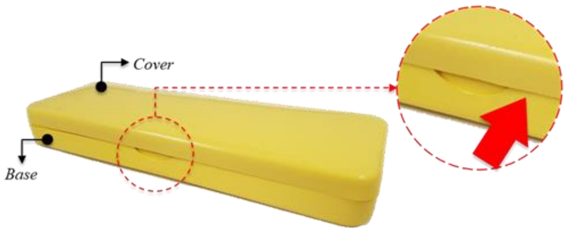

Fig. 1. Warpage defects on pencil box

Measurement of the amount of surface deviation due to warpage can be performed, one of which is by using Moldflow. Fig. 2 explains that the maximum deflection at the base

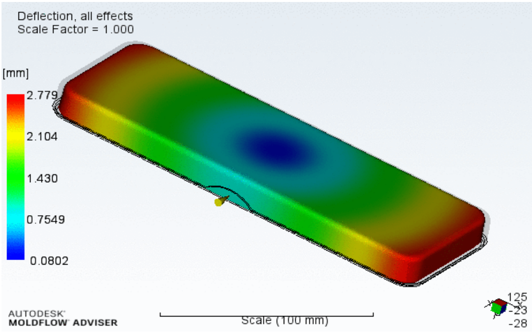

Fig. 2. Simulation result of warpage at base

It shows that there is a warpage defect that occurs in the base of the pencil box. The largest deflection value generated by the Moldflow simulation is 2.779 mm.

II. RESEARCH METHODS

A. Research Flow

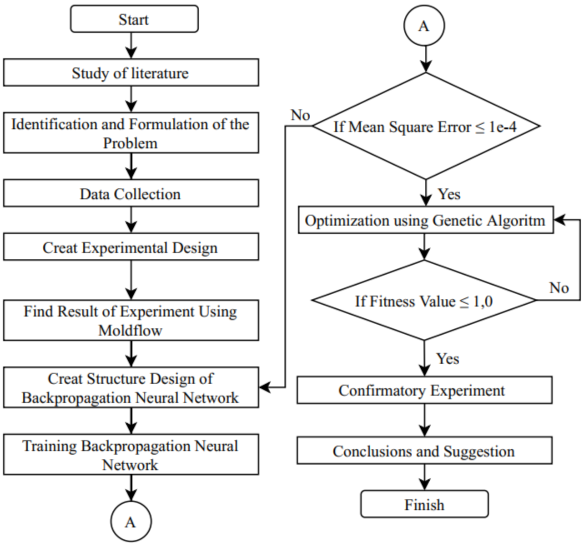

Fig. 3. Flowchart of warpage defect optimization on base

Refering to Fig. 3, the data will be taken from the design of the pencil box product, the sheet of plastic material, the sheet of mold and from trial & error. From these data, an experimental design was carried out using an orthogonal matrix L_{27} (3^4) [6]. The simulation process was initially proven by Moldflow to obtain warpage data that occurred. Data training was carried out using Backpropagation Neural Network (BPNN) to identify the pattern of the relationship between process parameters and response [7, 8]. Genetic algorithm (GA) optimization method is used to determine variations in process parameter settings that can optimize warpage defects [9]. The validation process is carried out by software simulation.

B. Previous Research

In the previous research conducted by the author, the testing process using MoldFlow on radiator cover products was carried out with a combination of parameters and a feed system to optimize the fill time value [10]. The application of the Backpropagation Neural Network method can use the MATLAB application program which is able to reduce iterations in the performance of the training algorithm. The process carried out for the Backpropagation Neural Network program is as follows [11]. Other studies have also been conducted to increase efficiency and flexibility by using a combination of these methods, which can be proposed for general use in optimizing defects of plastics [12].

C. Data Collection

Technical information is in the form of plastic material data by using PP7555KNE2 ExxonMobil, mold specifications of pencil box, Injection of Molding Machines Hwa Chin 160 SE and injection of simulation parameters. The following is the data used in the simulation process as shown in Table 1-5.

- Testing Parameters

TABLE I
FIRST PARAMETER OF PLASTIC BOX TESTING

No	Parameter	Factor Level		
		-1	0	1
1	Mold temperature (°C)	15,5	32,5	49,5
2	Melt temperature (°C)	200	225	250
3	Packing pressure (%)	80	100	120
4	Injection time (second)	0.05	3,3	6,6

TABLE II
SECOND PARAMETER OF PLASTIC BOX TESTING

No	Parameter	Factor Level		
		-1	0	1
1	Mold temperature (°C)	19,75	32,5	45,25
2	Melt temperature (°C)	206,25	225	243,75
3	Packing pressure (%)	85	100	115
4	Injection time (second)	0,9	3,3	5,8

TABLE III
THIRD PARAMETER OF PLASTIC BOX TESTING

No	Parameter	Factor Level		
		-1	0	1
1	Mold temperature (°C)	24	32,5	41
2	Melt temperature (°C)	212,5	225	237,5
3	Packing pressure (%)	90	100	110
4	Injection time (second)	1,7	3,3	5

- Constant Parameters

TABLE IV
CONSTANT PARAMETER

No	Parameter	Value	Unit
1	Max. machine injection pressure	160	MPa
2	Packing time	10	Second
3	Machine clamp open time	5	Second
4	Cooling time	30	Second
5	Injection gate location	1	Point
6	Gate contact diameter	2	mm
7	Velocity/pressure switch-over	99	%
8	Analysis resolution	2	Level
9	Plastics material	PP	-

- Degree of Freedom

TABLE V
DEGREE OF FREEDOM FOR VARIABLE PROCESS AND LEVEL

No	Variable Process	Number of Level *(k)*	$V_{fl} = (k-1)$
1	Mold temperature (°C)	3	2
2	Melt temperature (°C)	3	2
3	Packing pressure (%)	3	2
4	Injection time (second)	3	2
	Total Degree of Freedom (V_{fl})		**8**

III. Results and Discussions

A. Data Analysis

The experiment was carried out by combining the process parameter variables contained in the MoldFlow. The process parameters used in this study were mold temperature, melt temperature, packing pressure and injection time. These parameters are then combined with 27 times experimental design and with 2 times replication and randomization in each test as shown in Table 6.

B. Data processing with Backpropagation Neural Network

- Pre-processing Data

Pre-processing is a form of initialization of experimental data which has different intervals and units into non-dimensional data whose intervals are determined between -1 to 1. This process is carried out on the input parameters and constants, namely as parameter data for the simulation process, with the output value generated from the simulation which is the maximum deflection on the surface of the base component on the pencil box [13].

- Network Determination

Network determination is significantly influenced by the functions that make up the network, so it is necessary to pay attention to the selection of functions used to simplify and speed up the training process. In this research, the functions used in the Backpropagation Neural Network are limited, namely the activation function and the training function. The signal from the neuron input whether it is up or not is greatly influenced by the activation function. So that the training function is also influenced by whether or not it is appropriate to select the function [13].

TABLE VI
RESULT OF SIMULATION

Exp. No.	Variable Process (X)				Response (Y)		
	Melt temp. (°C)	Mold temp. (°C)	Pack press. (%)	Inj.time (second)	1st Deflection (mm)	2nd Deflection (mm)	3rd Deflection (mm)
1	15	200	60	0.01	1.288	1.23	1.232
2	15	200	90	3.01	1.629	1.589	1.600
3	15	200	120	6	1.566	1.588	1.602
4	15	225	60	3.01	1.764	1.827	1.811
5	15	225	90	6	1.666	1.69	1.680
6	15	225	120	0.01	1.211	1.192	1.174
7	15	250	60	6	1.730	1.968	1.937
8	15	250	90	0.01	1.689	1.723	1.705
9	15	250	120	3.01	1.838	1.891	1.856
10	35	200	60	3.01	1.766	1.745	1.784
11	35	200	90	6	1.692	1.728	1.716
12	35	200	120	0.01	0.903	1.126	1.141
13	35	225	60	6	1.905	1.942	1.926
14	35	225	90	0.01	1.304	1.534	1.479
15	35	225	120	3.01	1.707	1.729	1.753
16	35	250	60	0.01	1.951	1.97	1.964
17	35	250	90	3.01	1.880	1.914	1.909
18	35	250	120	6	1.870	1.905	1.894
19	55	200	60	6	1.783	1.776	1.795
20	55	200	90	0.01	1.245	1.286	1.268
21	55	200	120	3.01	1.636	1.632	1.637
22	55	225	60	0.01	1.645	1.836	1.828
23	55	225	90	3.01	1.752	1.787	1.782
24	55	225	120	6	1.897	1.939	1.940
25	55	250	60	3.01	1.930	1.953	1.946
26	55	250	90	6	1.983	2.054	2.025
27	55	250	120	0.01	1.818	2.09	2.089

- Number of Neurons on Hidden Layer

The results of Backpropagation Neural Network training obtained are influenced by the number of neurons and hidden layers used (Table 7), so it needs to be considered in determining the number [14].

TABLE VII
NUMBER OF NEURON

No	Number of Neurons
1	2
2	4
3	8
4	9

- Network Initialization

Network formation in Backpropagation Neural Network is done by adding a hidden layer to the network. However, the network needs to be initialized first by adding an activation function and a training function. In this research, the activation function used is the "tansig" function and the "logsig" function, while the training function uses the "trainrp" function [14].

- Initialize Weight and Bias Values

The network formation process is carried out by adding weight and bias values to each network. The process of adding it starts from a small number randomly. However, if the weight and bias values are determined, it can also be done by giving the values directly [13].

- Stopping Criterion (Table 8)

TABLE VIII
STOPPING CRITERION

No.	Script	Value
1	net.trainParam.epochs	100000
2	net.trainParam.time	50000
3	net.trainParam.goal	1e-4
4	net.trainParam.min_grad	1e-20
5	net.trainParam.max_fail	10

- Percentage of Training Data and Test Data (Table 9)

TABLE IX
PERCENTAGE OF DATA

No	Script	Percentage	Total Data
1	net.divideParam.TrainRatio	80%	65 data
2	net.divideParam.valRatio	0%	0 data
3	net.divideParam.testRatio	20%	16 data

- Learning Rate

Learning rate is one of the training parameters on a network that is used to calculate the weight correction value. In principle, the smaller the learning rate value used, the more precise the algorithm will be. Likewise, if the learning rate value used is large enough, the algorithm results obtained are less precise. However, a learning rate value that is too small will have an impact on the estimated training that is getting longer and requires a large enough storage memory. So, with these limitations, this study uses the value of the learning rate, namely 0.01 [13].

- Network Architecture Forms

Based on the calculations performed using MATLAB, the smallest mean square error value is 0.000099699 in experiment 7^{th}. So that the Backpropagation Neural Network architectural formation that is formed consists of 2 hidden layers, 9 neurons, the activation function "tansig" and the training function "trainrp". The form of network architecture resulting from these calculations is shown in Table 10 and Fig. 4 – 5 as follows [15].

TABLE X
COMBINATION OF ERROR CALCULATION PARAMETERS

No	Hidden Layer	Number of Neurons	Activation Function	Training Function	Max. Epoch	Epoch	Mean Square Error
1	2	2	Tansig	Trainrp	100000	99999	0.019633200
2	2	2	Logsig	Trainrp	100000	100000	0.025627700
3	2	4	Tansig	Trainrp	100000	52893	0.000009999
4	2	4	Logsig	Trainrp	100000	100000	0.000117604
5	2	8	Tansig	Trainrp	100000	1103	0.000099813
6	2	8	Logsig	Trainrp	100000	791	0.000099706
7	**2**	**9**	**Tansig**	**Trainrp**	**100000**	**534**	**0.000099699**
8	2	9	Logsig	Trainrp	100000	1153	0.000099860

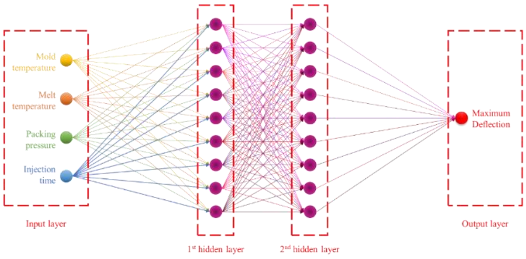

Fig. 4. Architecture of network formation 4-9-9-1

- Backpropagation Neural Network Results

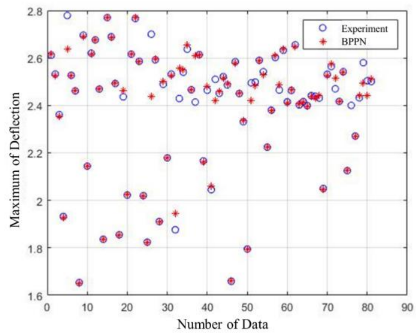

Fig. 5. Error training trial 7^{th}

The Error Training graph shows a pattern formed from experimental data and training data from Backpropagation Neural Network as shown in Table 11. The purpose of this training process is fulfilled, indicated by the achievement of the maximum performance value or mean square error of 0.00000999345.

TABLE XI
COMPARISON OF EXPERIMENTAL AND BPPN TRAINING DATA

No	Type of Error	Percentage of Error
1	Minimum	0 %
2	Maximum	11 %
3	Average	0.76 %
4	Standard deviation	0.020851

C. Optimization of Response Parameters Using Genetic Algorithm Method

The optimization method carried out with the Genetic Algorithm is used to find the optimal parameter composition as shown in Table 12, so as to minimize warpage defects that occur in base of pencil box. This optimization process is continued with the previous process, namely using training data as the basis for calculations. However, there are several steps that need to be taken in this process, such as: determining the limits of the parameters, representing the chromosomes, determining the fitness function, and determining several options in MATLAB [16].

TABLE XII
VARIABLE LIMIT OF THE GA TESTING PROCESS

Parameter	Unit	Limit		Interval
		Maximum	Minimum	
Mold temperature	(°C)	15.5	49.5	34
Melt temperature	(°C)	200	250	50
Packing pressure	(%)	80	120	40
Injection time	(second)	0.05	6.6	6.55

- Determination of Process Parameter Boundaries

The limit value in the simulation process parameter is determined by the maximum and minimum values of each process variable [17].

- Representation of Each Chromosome

One of the optimization processes in Genetic Algorithm is done by regenerating the chromosomes that were previously available. This regeneration process is carried out by means of crossover and mutation [18].

- Determination of Fitness Functions

In the Genetic Algorithm method, the process of determining the target is done by positioning the optimal conditions of the parameters themselves, so that the process of placing these conditions becomes a critical point in this analysis [17].

- Determination of the Options Structure

Genetic algorithm options structure (Table 13) consists of several options to solve problems in optimization. The MATLAB "gaoptimset" function is used as an option to perform these calculations [13].

- Result of Optimization of Genetic Algorithm

Based on these parameter recommendations (Table 14), the values of the mold temperature is 15°C, melt temperature is 200°C, packing pressure is 120% and injection time is 6 seconds.

TABLE XIII
GENETIC ALGORITHM OPTIONS

No.	Structure Options	Value
1	Population Size	150
2	Generations	20
3	Elite Count	50
4	Pareto Fraction	0.8
5	Crossover Fraction	0.6
6	Migration Fraction	0.4
7	Tol Fun	1e-8
8	Method	RWS

TABLE XIV
RECOMMENDED PARAMETERS

No	Parameter	Value
1	Mold temperature	15 °C
2	Melt temperature	200 °C
3	Packing pressure	120 %
4	Injection time	6 second

D. Confirm Trial

Experimental confirmation is carried out to ensure the parameters recommended by the Genetic Algorithm are optimal to minimize warpage defects that occur in pencil box products. Table 15 is the composition of the parameters tested.

TABLE XV
OPTIMAL COMPOSITION

No	Parameter	Value	Result
1	Mold temperature	15 °C	1,554
2	Melt temperature	200 °C	1,558
3	Packing pressure	120 %	1,578
4	Injection time	6 second	1,578
			1,578

The simulation results carried out in the Autodesk MoldFlow Adviser with the optimal parameter recommendations from the results of the optimization process using the Genetic Algorithm Method are shown in Fig. 7.

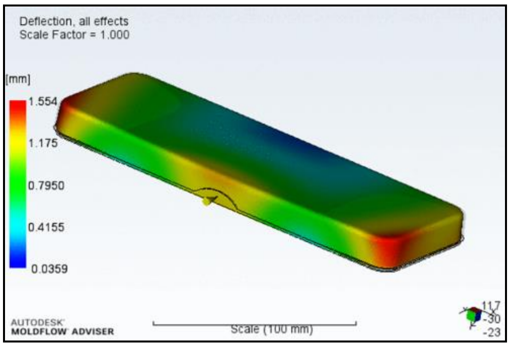

Fig. 7. Deflection optimization results on pencil box

IV. Conclusions and Reccomendations

A. Conclusions

The results of the research carried out by optimizing the parameters of the injection molding simulation process to minimize warpage defects in base of pencil box products can be achieved with the following results.

1) Warpage defects in pencil box products can be reduced by 44% from 2.779 mm to 1.554 mm.
2) The optimal parameters for the simulation process of injection molding on pencil box products are mold temperature of 15°C, melt temperature of 200°C, packing pressure of 120% and injection time of 6 second.

B. Recommendations

Research on warpage defects currently carried out on pencil box products requires continuous research, the goal is to get more optimal results than before. One that has a significant role in eliminating these defects apart from optimization of the parameters is by adding ribs to the surface area that has the largest warpage defect. Although the use of ribs has visual and functional shortcomings in these products, they can be minimized by adjusting the ideal size to the condition of the product

References

[1] D. V. Rosato, D. V. Rosato, and M. V. Rosato, *Plastic Product Material and Process Selection Handbook*. September. 2004.

[2] D. Braun, "Poly(vinyl chloride) on the way from the 19th century to the 21st century," *J. Polym. Sci. Part A Polym. Chem.*, 42 (3), pp. 578–586, 2004, doi: 10.1002/pola.10906.

[3] D. V. Rosato, D. V. Rosato, and M. G. Rosato, *Injection Molding Handbook*, Third Edit, Kluwer Academic Publishers: USA, 2000.

[4] J. M. Fischer, *Handbook of Molded Part Shrinkage and Warpage: Second Edition*. 2012.

[5] J. M. Fischer, *Handbook of Molded Part Shrinkage and Warpage*. Norwich, United States of America: Plastics Design Library/William Andrew, Inc, 2003.

[6] Y. Gao and X. Wang, "An effective warpage optimization method in injection molding based on the Kriging model," *Int. J. Adv. Manuf. Technol.*, 37 (9–10), pp. 953–960, 2008, doi: 10.1007/s00170-007-1044-6.

[7] M. A. Arbib, *The Handbook of Brain Theory and Neuron Network*, 2nd Edition., The MIT Press: England, 2015.

[8] F. Yin, H. Mao, L. Hua, W. Guo, and M. Shu, "Back propagation neural network modeling for warpage prediction and optimization of plastic products during injection molding," *Mater. Des.*, 32 (4), pp. 1844–1850, 2011, doi: 10.1016/j.matdes.2010.12.022.

[9] F. Yin, H. Mao, and L. Hua, "A hybrid of back propagation neural network and genetic algorithm for optimization of injection molding process parameters," *Mater. Des.*, 32 (6), pp. 3457–3464, 2011, doi: 10.1016/j.matdes.2011.01.058.

[10] E. A. Wibowo, A. Syahriar, and A. Kaswadi, "Analysis and simulation of short shot defects in plastic injection molding at multi cavities," *ICONETSI Int. Conf. Eng. Inf. Technol. Sustain. Ind.*, pp. 1–6, 2020, doi: 10.1145/3429789.3429837.

[11] P. Kim, *MATLAB Deep Learning: With Machine Learning, Neural Networks and Artificial Intelligence*. 2017.

[12] H. Kurtaran, B. Ozcelik, and T. Erzurumlu, "Warpage optimization of a bus ceiling lamp base using neural network model and genetic algorithm," *J. Mater. Process. Technol.*, 169 (2), pp. 314–319, 2005, doi: 10.1016/j.jmatprotec.2005.03.013.

[13] J. J. Siang, *Jaringan Syaraf Tiruan dan Pemrogramannya Menggunakan Matlab*, Edisi Andi Publisher: Yogyakarta, 2005.

[14] R. M. Hristev, *The ANN Book*, 1st Editio. GNU Public License, ver. 2, 1998.

[15] Mathworks, "*Computation Visualization Programming Getting Started with MATLAB The Language of Technical Computing*," 1984, [Online]. Available: www.mathworks.com.

[16] W. Guo, F. Deng, Z. Meng, L. Hua, H. Mao, and J. Su, "A hybrid back-propagation neural network and intelligent algorithm combined algorithm for optimizing microcellular foaming injection molding process parameters," *J. Manuf. Process.*, 50, pp. 528–538, 2020, doi: 10.1016/j.jmapro.2019.12.020.

[17] T. D. Salamoni and A. Wahjudi, "Injection molding process modeling using back propagation neural network method," *AIP Conf. Proc.*, vol. 1983, 2018, doi: 10.1063/1.5046266.

[18] A. Dutta, "Crossover in Genetic Algorithm - GeeksforGeeks," *Geeks for Geeks*, pp. 1–7, 2021, [Online]. Available: https://www.geeksforgeeks.org/crossover-in-genetic-algorithm/.